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Human pulses reveal health conditions by a piezoelectret sensor via the approximate entropy analysis

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ABSTRACT

A piezoelectret pulse sensor combined with the approximate entropy (ApEn) analysis is utilized to detect human pulses to reveal health conditions. Inspired by the traditional Chinese medicine (TCM) with a foundation of more than 2500 years, human pulses are helpful in the diagnostics of illness as the body’s vital energy circulates through blood vessels with branches connected to organs. A flexible cellular polypropylene (PP) piezoelectret film with a wooden cylinder substrate is used to emulate the pulse taking process in TCM to record the pulse characteristics. A group of 26 volunteers have been successfully diagnosed by the wearable sensing system and the approximate entropy analysis has been implemented to analyze the data. Results show a threshold approximate entropy value of 0.1 as the separation point between the volunteers of normal and abnormal health conditions.

1. Introduction

Pulse manifestation is one of important tools in the traditional Chinese medicine (TCM) practice by well-trained doctors to identify potential human health problems. As blood travels around the whole body, the health states of organs and body parts are often reflected in the pulse appearances via the dynamic pressure changes from the contraction and relaxation of the heart and the flow of blood through the arteries [1–3]. Today, researchers have studied many physiological parameters of the human body through the analyses of pulse signals, such as pulse wave velocity, amplitude, waveform, and so on to provide valuable human health information such as the degree of hardening of human blood vessels, changes in blood pressure and heart rate, etc [2–4].

In recent years, various pulse sensors have been proposed for the measurement of pulse waves, such as optical sensors, piezoresistive sensors, pressure sensors, acoustic sensor, piezoelectric sensors, image sensors, capacitance-based sensors, and piezoelectret sensors [5–14]. Among these, piezoelectret sensors can have a high equivalent piezoelectric coefficient $d_{33}$ for high sensitivity [15–20]. The piezoelectric properties are derived from the stored charges in the material voids inside cellular PP is difficult to be homogeneous as voids are formed with an uncontrolled thermal expansion method [21,25]. The un-uniform voids will affect the uniformity of piezoelectricity.

Moreover, it’s important to combine a self-powered piezoelectret wearable sensing system with an accurate and improved data analysis method to understand the real physiological conditions of human body. Physiologic systems are regulated by interacting mechanisms that
operate across multiple spatial and temporal scales. The output variables of these systems often exhibit complex fluctuations that are not simply due to “contaminative” noise but contain information about the underlying dynamics. Traditional entropy-based algorithms quantify the regularity of a time series. Entropy increases with the degree of disorder and is maximum for completely random systems. However, an increase in the entropy may not always be associated with an increase in dynamical complexity [28,29]. In this work, the cellular PP piezoelectret film with $d_{33}$ value of 510 pC/N is utilized for pulse sensing and the scheme of approximate entropy analysis is used to analyze the pulse data for the diagnosis of human health and the results are represented and compared with known health conditions of volunteers, in which an ApEn value of 0.1 is the threshold for the health state.

2. Results and discussion

2.1. Design of the pulse sensing system

Fig. 1a shows the main arterial distributions in the human body [13] and the sensing system proposed in this paper is used to obtain the pulse signals through the radial artery at the wrist portion. For the pulse taking practice in TCM, the position is at the wrist in the posterior part of the radial artery as the body’s meridians are brought together and at the wrist for pulse diagnoses in the traditional Chinese medicine (TCM). (b) The pulse taking process by well-trained doctors practicing in TCM using three fingers as the sensing devices. (c) Proposed pulse sensor structure with a cylinder-shape wood piece (to assure the intimate contact between the sensor and skin), top electrode, piezoelectret film, and bottom electrode. (d) Piezoelectret pulse sensing system with a mechanical fixture (green) and a clamp used in the pulse taking tests. The cylinder-shape wood pieces are utilized to fix the sensor and the skin for stable pulse readings.

2.2. Working principle and setup of the pulse sensing system

The cellular PP film structure has the advantages of large equivalent piezoelectric coefficient, good flexibility and light weight such that it is chosen in this work and is fabricated with the thermal expansion method [21,25]. The thickness of a typical cellular PP film is 170 µm with oval-shaped air bubbles of tens of micrometers in diameter as shown in the cross-sectional SEM image in Fig. 2a. In theory, the stacking air bubbles and PP polymer could be regarded as many parallel-plate capacitors connected in series, as shown in Fig. 2b. After the corona charging process [30], the air in the air bubbles can be broken down and the ionized charges are captured by the surfaces of the cavities in the PP film. The positive charges (+$\sigma_n$) and negative charges ($-\sigma_n$) from electrical dipoles. If electrodes are added on both the top and bottom surfaces of the film, a sensor is constructed. The positive and negative charges inside the cellular PP film will be induced with the corresponding induced charges of $+\sigma$ and $-\sigma$ on the electrodes. When the sensor was compressed in Fig. 2c and released in Fig. 2d, the diameter of the air bubbles changes and the moments of electrical dipoles
are also simultaneously changed. As a result, the electrical potential between the two electrodes are not in equivalent states to drive the external current flow.

The equivalent quasi-static piezoelectric coefficient \( d_{33} \) of a typical cellular PP piezoelectret film (with electrodes, placed in laboratory atmosphere for 4 weeks) has been measured by a weight-moving method, as indicated in Fig. 2e. Specifically, a mass with a given weight (70 g) is placed on a sample and a known force \( F = 0.7 \text{ N} \) is applied on the sample and the mass is removed afterwards. As a result, a positive current peak is generated and the measured peak value is 15.08 nA. By integrating the resulted current curves, the amount of transferred charges is obtained at about 360 pC in the prototype test, as shown in Fig. 2f. The quasi-static \( d_{33} \) value is calculated by following formula [30]:

\[
\text{Quasi-static } d_{33} = \frac{Q}{F}
\]

The quasi-static \( d_{33} \) value is obtained at about 510 pC/N.

The measurement system setup is illustrated in Fig. 2g. It consists of the pulse sensor, current preamplifier (Stanford Research Systems, SR570), data acquisition card (NI USB-602) and personal computer (PC). During the test, the output signal of the pulse sensor is amplified via a current preamplifier. The magnification factor of the current amplifier is 50 pA/V. The data acquisition card can realize the analog to digital conversion of the signal and transmit the collected signal data to the PC. The sampling rate in the experiment is 60 Hz/s. The signals display and data storage are realized through the LabVIEW. The stored data is further processed and analyzed using MATLAB. The 26 volunteers are between 22 and 25 years old, with 16 males and 10 females.
with reports of their physical health conditions provided by a local hospital.

2.3. Approximate entropy for pulse waves analysis

The concept of approximate entropy (ApEn) analysis was proposed by Pincus in the 1990s to overcome the difficulty of solving entropy in chaos [31]. It measures the probability of generating new patterns in the signal from the perspective of nonlinear time series complexity. The ApEn reflects the similar probability difference of a polygonal chain between the conditions when the polygonal chain related to m points and the conditions with m + 1 point. The ApEn demonstrates the generation possibility of new modes when the dimension is increased from m to m + 1 with the occurrence rate of new information in the time series. The larger of the ApEn value is, the greater the probability of generating a new pattern is, and the more complex of the sequence. Some researchers have established a quantitative relation between the ApEn value of brain wave signals and epilepsy, and achieved automatic diagnosis and prediction of epilepsy [32]. Researchers have also used dynamic ApEn maps as a tool for the atrial fibrillation rotor mapping [33]. In addition, the ApEn analysis method has also been used for the diagnosis and treatment of other diseases such as cardiac abnormalities, eye diseases, early diabetes, Alzheimer’s disease, autism, fatty liver, and stroke [34]. A lot of studies show that the ApEn can be used to characterize changes in human physiological conditions. Because a robust estimate can be obtained with a small data set of less than 50 by using ApEn calculation, it is particularly useful for non-stationary biological signals. The implementation of the ApEn algorithm can be described as follows.

For the time series \( \{x(i)\} \) with a data length of N (generally between 75 and 5000), the m-dimensional space reconstruction is performed, and the reconstructed i-th vector is expressed as follows:

\[
X(i) = \{x(i), x(i + 1), ..., x(i + m - 1)\} \quad (i = 1, 2, 3, ..., N - m + 1)
\]

(2)

Where \( m \) is the pre-selected mode dimension, usually \( m = 2 \). The distance \( d[X(i), X(j)] \) between \( X(i) \) and \( X(j) \) is defined as the largest difference between the two corresponding elements. The relationship was exhibited in Eq. (3):

\[
d[X(i), X(j)] = \max_{0 \leq k < m} |x(i + k) - x(j + k)|
\]

(3)

The space distance \( d[X(i), X(j)] \) between \( X(i) \) and the other vector \( X(j) \) can be calculated. Given the threshold \( r \), usually \( r = 0.1-0.2 \)SD (SD is the standard deviation of the sequence \( \{x(i)\} \)). The number of \( d[X(i), X(j)] \) less than \( r \) is calculated for each \( i \), and the ratio of the number and the total distance \( (N-m) \) is also calculated which is marked as \( C^m_i \). Then take logarithm of \( C^m_i \) and take the average of all \( i \), denoted as \( \Phi^m(r) \).

\[
\Phi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \ln C^m_i(r)
\]

(4)

Increasing the \( m \) by 1 to become \( m+1 \) dimension and repeating the above steps to get \( C^{m+1}_i \) and \( \Phi^{m+1}(r) \), one can obtain the approximate entropy as shown in Eq. (5):

\[
ApEn = \Phi^m(r) - \Phi^{m+1}(r)
\]

(5)

In this experiment, the sample rate is set as 60 Hz/s and the collection time was 60 s. During the calculation of ApEn, the \( m \) is set as 2 and the \( r \) is 0.15 SD. Each 600 points is used for ApEn calculation and 6 values of ApEn were acquired in each time.

To obtain a stable pulse signal by the flexible piezoelectric sensing system, we fix the contact force between the piezoelectric film and human skin so that the binding force of each measurement is same. We also analyze the pulse signals obtained under different force conditions as shown in Fig. 3. Specifically, different forces are applied through a medical fixation clamp, which has 3 fixed forces. 3 different forces are marked as deep, middle and superficial, respectively.

Firstly, the time domain pulse signals under different force magnitudes of deep, middle and superficial strength are collected as shown in Fig. 3a to c. It can be seen that the greater the force, the larger the voltage generated by the sensing system as illustrated in Fig. 3d.

Fig. 3. Sensing performances under different applied force. (a-d) Time domain signals and (e-g) frequency domain pulse signals under different applied force magnitudes of deep, middle and superficial strength.
Signals from deep, middle and superficial regions than 0.04. The average values of the approximate entropy of the three groups of signals are less than 0.013. This result shows that the magnitude of force acting on the skin has little effect on the composition and complexity of the pulse signal using the ApEn algorithm. As such, the subsequent tests used only the middle force in the rest of the paper.

When the pulse signal measurement is performed on the human body, it is clinically required to perform the measurement when the physical condition of the volunteer is relatively calm. The reason is that the body will increase the load of the heart after being stimulated or exercised, thereby affecting the inherent complexity of the pulse signal. To verify the ApEn algorithm can effectively identify the abnormal state of the heart, the pulse data from a healthy volunteer at normal state, after exercise, and thirty minutes of rest after exercise are collected, respectively as shown in Figs. 4b to 4d. It can be found that the 6 ApEn values of the pulse signal after strenuous exercise are all less than 0.1, and the ApEn values are all around 0.35 before exercise and thirty minutes after exercise. During physical exercise, there is a sustained increase in heart rate and a decrease in the amplitude of the interval fluctuations in response to an increased demand for oxygen and nutrients. The dynamics is, therefore, limited to a subset of the state space. We anticipate that under a variety of stressed conditions, healthy systems will generate fewer complex outputs than those under free-running conditions. Therefore, the approximate entropy value of the pulse signal after exercise is smaller than that in the free-running state [35]. From this test result, it can be qualitatively observed that the characteristics and complexity of the human pulse signal will change greatly after being stimulated.

2.4. Health condition analysis with ApEn

To quantitatively use the ApEn value as a guideline for the human health analyses, we select a group of volunteers without sinus arrhythmia as the reference and a group volunteers with known sinus arrhythmia issue as diagnosed by a local hospital as the research objects for the physical examinations by taking the pulse measurements as shown in Fig. 5a to d. It can be found that there are obvious differences in the waveform characteristics between the two groups of signals in signal waveforms of both the time-domain and frequency-domain results. However, it is difficult to extract useful criteria to differentiate these signals.

Subsequently, ApEn calculations are performed on these signals and 6 approximate entropy values for the two volunteers are obtained in Fig. 5e. From the statistics of ApEn values, it can be seen that the values for the volunteer with the known sinus arrhythmia condition are between 0.05 and 0.07, while the ApEn values for the healthy volunteer are between 0.28 and 0.33, with a difference of an order of magnitude is observed between the two volunteers. Previously, some studies have found that the physiologic complexity is associated with the ability of living systems to adjust to an ever-changing environment, which requires the integrative multiscale functionality [28]. In contrast, under the free-running condition, a sustained decrease in the ApEn value reflects a reduced ability for the system to function in certain dynamical regimes - possibly due to decoupling or degradation of the body control mechanisms. As such, the reduced complexity could result in potential manifestation of pathologic dynamics such that the volunteer with the sinus arrhythmia condition has much lower ApEn values as compared with those of the healthy volunteer as demonstrated.

Moreover, we calculate and summarize the ApEn values from the pulse data of all the 26 volunteers by taking 6 ApEn values and averaging them for each volunteer as shown in Fig. 6a, arranged in the descending order. The 26 volunteers are between 22 and 25 years old, with 16 males and 10 females with reports of their physical health conditions provided by a local hospital. It is found that the ApEn values are less than 0.1 for 6 volunteers, of which one volunteer is a known sinus arrhythmia patient. By checking the physical examination reports of the volunteers provided by a local hospital, it is revealed that 6 out of them have arrhythmia issues.
26 volunteers have various degrees of illness with poor physical health (including the one with the sinus arrhythmia condition). The health states and ApEn values of the 6 volunteers are shown in Fig. 6b as two of them have varying degrees of sinus arrhythmia, two have flu, one has upper respiratory tract infection, and one has insomnia. The flu and upper respiratory tract infections can cause paroxysmal supraventricular tachycardia to result in increased heart load and this could lead to changes in the complexity of the pulse signals. Furthermore, there is clinical evidence that some insomnia patient may sleep less than four hours at night to cause the increase in the blood pressure and result in increased heart load. Therefore, it can be inferred that insomnia also increases the burden on the heart, resulting in the change in of the pulse signal. The health condition of the human body is largely associated with the heart and will be reflected in HP signals. Under pathologic conditions, the structure of the time series variability may change in two different ways. One dynamical route to disease is associated with loss of variability and the emergence of more regular patterns (e.g., heart failure). The other dynamical route is associated with more random types of outputs (e.g., atrial fibrillation). In both cases, MSE reveals a decrease in system complexity [29]. Pulse taking diagnosis has always been used as a major diagnostic method in TCM, because TCM has always believed that the pulse can reflect the characteristics of many human health conditions.

From the heart rate analyses of the 26 volunteers using the piezoelectret sensing system (see Table. S1), it is found that the heart rates of healthy and unhealthy volunteers are similar except for patients with sinus arrhythmia whose heart rates are greater than 100 beats per minute, while the others are within the normal range of 60–100 beats per minute. In other words, the heart rate itself may be able to identify patients with potential sinus arrhythmia problems but won’t be able to reveal other health conditions. Furthermore, by comparing the test results with the physical examination report of the volunteer (Table. S1), it is found that the heart rate itself may be able to identify patients with potential sinus arrhythmia problems but won’t be able to reveal other health conditions. Furthermore, by comparing the test results with the physical examination report of the volunteer (Table. S1), it is found that the heart rate itself may be able to identify patients with potential sinus arrhythmia problems but won’t be able to reveal other health conditions. Furthermore, by comparing the test results with the physical examination report of the volunteer (Table. S1), it is found that the heart rate itself may be able to identify patients with potential sinus arrhythmia problems but won’t be able to reveal other health conditions.
S1), it can be shown that the sensing system is very accurate in obtaining the human heart rate.

This work shows that if the ApEn value is less than 0.1, the health condition of the volunteer could be in question. Although these criteria are concluded from the 26 volunteers, the consistency is very good, while further systematic study could provide better statistical values. Furthermore, while the proposed methodology cannot quantitatively diagnose the type of disease, it does provide qualitatively the health conditions of the volunteer. It is believed that further studies of more pulse data from a large group of volunteers with advanced approaches in data analysis such as machine learning or others could eventually provide better diagnoses of human health conditions similar to the ancient practices of TCM.

3. Conclusion

In this study, the piezoelectric pulse sensing system is utilized to gather pulse data with the ApEn algorithm on 26 volunteers. It is found that the ApEn value can be used to evaluate the health condition of human body. In the case volunteers with poor health, the individual adaptability will decline to result in the decrease of ApEn value. According to the statistics results of this work, an ApEn value of 0.1 is the threshold for the health state. Furthermore, it has been verified through experiments that the ApEn values won’t change for pulse signals obtained under different magnitudes of applied forces during the pulse measurements. As such, the sensing system could provide convenient operation procedures to obtain the pulse data for analyses with low degree of distortions.

4. Experiments

4.1. Characterisation

The morphology of the samples is examined via Field Emission Scanning Electron Microscope (SEM, FEI Nova NanoSEM 450). The outputs of the devices are measured by a Stanford low-noise current preamplifier (Model SR570) and NI PCI-6259 DAQ.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.nanoen.2019.01.092.

References


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